Contract No.: 53-3198-6-017
MPR Reference No.: 8370-029

Using Bayesian Shrinkage Methods to Derive State Estimates of Poverty, Food Stamp Program Eligibility, and Food Stamp Program Participation

March 13, 1998

Allen L. Schirm
John V. DiCarlo

Submitted to:

U.S. Department of Agriculture
Food and Nutrition Service
3101 Park Center Drive
2nd Floor
Alexandria, VA 22302

Project Officer:
Jenny Genser

Submitted by:

Mathematica Policy Research, Inc.
600 Maryland Avenue, SW
Suite 550
Washington, DC 20024-2512
(202) 484-9220

Project Director:
Carole Trippe

This work was prepared as one task of a competitively awarded contract, the total amount of the contract is $3,102,189.

CONTENTS

Chapter		Page
	EXECUTIVE SUMMARY	ix
I	INTRODUCTION	1
II	A STEP-BY-STEP GUIDE TO DERIVING STATE POVERTY ESTIMATES	5
III	STATE ESTIMATES OF POVERTY, FSP ELIGIBILITY, AND FSP PARTICIPATION FOR 1994	17
	REFERENCES	23
	APPENDIX A: THE ESTIMATION PROCEDURE: ADDITIONAL TECHNICAL DETAILS	A-1

TABLES

Table		Page
II.1	1994 POVERTY RATES	8
II.2	PRELIMINARY SHRINKAGE ESTIMATES OF THE NUMBERS OF POOR PEOPLE IN 1994	15
III.1	FINAL SHRINKAGE ESTIMATES OF THE NUMBERS OF POOR PEOPLE AND POVERTY RATES IN 1994	18
III.2	APPROXIMATE 90-PERCENT CONFIDENCE INTERVALS FOR SHRINKAGE ESTIMATES OF POVERTY	19
III.3	FINAL SHRINKAGE ESTIMATES OF THE NUMBERS OF PEOPLE ELIGIBLE FOR FOOD STAMPS AND FOOD STAMP PARTICIPATION RATES IN JANUARY 1994	20
III.4	APPROXIMATE 90-PERCENT CONFIDENCE INTERVALS FOR SHRINKAGE ESTIMATES OF FOOD STAMP ELIGIBILITY AND PARTICIPATION	21

FIGURES

Figure		Page
II.1	THE ESTIMATION PROCEDURE	6
II.2	AN ILLUSTRATIVE REGRESSION ESTIMATOR	9
II.3	SHRINKAGE ESTIMATION	13

EXECUTIVE SUMMARY

The Food Stamp Program is a central component of American policy to reduce poverty and hunger. The program's main purpose is "to permit low-income households to obtain a more nutritious diet . . . by increasing their purchasing power" (Food Stamp Act of 1977, as amended). The Food Stamp Program is the largest of the domestic food and nutrition assistance programs administered by the U.S. Department of Agriculture's Food and Nutrition Service. During fiscal year 1997, the program served about 23 million people in an average month at a total annual cost of nearly $20 billion. The average monthly food stamp benefit was just over $170 per household.

This report presents estimates that, for each state, measure the need for the Food Stamp Program and its effectiveness in 1994. Specifically, the estimates of the number of poor people, the poverty rate, and the number of people eligible for food stamps measure the severity of economic deprivation in every state. The estimated food stamp participation rates measure, state by state, the program's performance in reaching its target population as of January 1994.

The estimates presented in this report were derived using Bayesian shrinkage estimation methods and data from the Current Population Survey, the Survey of Income and Program Participation, the decennial census, and administrative records. The shrinkage estimator for food stamp eligibles, for example, averaged sample estimates of eligibles in each state with predictions from a regression model. The predictions were based on observed indicators of socioeconomic conditions in the states, including levels of participation by state residents in government means-tested programs, such as the National School Lunch Program and the Aid to Families with Dependent Children program. The shrinkage estimates derived are substantially more precise than direct sample estimates from the Current Population Survey or the Survey of Income and Program Participation, the best sources of current data on household incomes. Shrinkage estimators improve precision by "borrowing strength," that is, by using data from all the states to derive each state's estimate and by using not only sample survey data but also census and administrative data.

I. INTRODUCTION

This report presents estimates of the number of poor people and the number of people eligible for food stamps in each state in 1994. It also presents estimates of state poverty rates and food stamp participation rates. All of our estimates were derived using "shrinkage" estimation methods. This introductory chapter overviews the advantages and some previous applications of shrinkage estimation. Chapter II describes how we derived shrinkage estimates, and Chapter III presents our state estimates of poverty and food stamp eligibility and participation. Technical details and additional information about our estimation methods are provided in the Appendix. The food stamp participation rate estimates presented here are also reported and compared with one another in Schirm (1998).

The principal challenge in deriving state estimates like those presented in this report is that the leading national surveys collecting current income data for families--the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP)--have small samples for most states. Thus, "direct" estimates from these surveys are imprecise. For example, because of the potential errors introduced by the CPS surveying only a small number of families in Oklahoma rather than all families in the state, we can be confident--according to widely used statistical standards--only that Oklahoma's poverty rate in 1994 was between about 13 and 21 percent. This range is fairly wide, reflecting our substantial uncertainty about what Oklahoma's poverty rate actually was.

Why small samples make direct estimates imprecise is easy to see. By the definition of "direct," a direct estimate is based on data from one source for the state and time period in question. Thus, a 1994 estimate for Oklahoma would be calculated using just 1994 data on one sample's households from Oklahoma. If 1994 data are collected for only a small number of Oklahoma households, as in the CPS or SIPP, direct estimates will be imprecise, that is, subject to substantial sampling error because the estimator uses only the information contained in the small sample. Therefore, as illustrated before, estimates of poverty rates will have large standard errors and wide confidence intervals, reflecting considerable uncertainty about the true extent of poverty.

To improve precision, statisticians have developed "indirect" estimators. These estimators "borrow strength" by using data from other states, time periods, or data sources. For example, two or three consecutive March CPS samples have been pooled (U.S. Department of Commerce 1996) to obtain larger samples for estimating state poverty rates.

A generally superior indirect estimator is the so-called "shrinkage" estimator. A shrinkage estimator averages estimates obtained from different methods. For example, Fay and Herriott (1979) developed a shrinkage estimator that combined direct sample and regression estimates of per capita income for small places (population less than 1,000). Their estimates were used to allocate funds under the General Revenue Sharing Program. Shrinkage estimators have also been used (see, for example, Schirm 1995, 1996) to develop state estimates of income-eligible infants and children for allocating funds under the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). To borrow strength across both space (states) and time, the current generation WIC eligibles estimator uses several years of CPS data and combines direct sample estimates with predictions from a regression model. The predictions of WIC eligibles are based on, for example, state per capita income and participation by state residents in programs such as Food Stamps, Aid to Families with Dependent Children (AFDC), and Unemployment Insurance. States with similar socioeconomic conditions, as reflected in per capita income or program participation statistics, are observed (and predicted) to have similar proportions of infants and children eligible for WIC. This contrasts with the direct estimator that ignores systematic patterns across states, using, for example, only Oklahoma data to derive an estimate for Oklahoma, even though conditions may be similar in Kansas. The shrinkage estimator uses data for all the states (with data for prior years and data from other sources) to estimate a regression model and formulate a prediction for Oklahoma. Then, the shrinkage estimator optimally averages the direct sample and regression estimates for Oklahoma to obtain a shrinkage estimate. In two other applications of shrinkage methods, state shrinkage estimates of median income for four-person families are used to administer the Low Income Home Energy Assistance Program (LIHEAP) (Fay, Nelson, and Litow 1993), while shrinkage estimates of poor school-aged children by county were used in allocating Title I compensatory education funds for disadvantaged youth for the current (1997-1998) school year (National Research Council 1998).

In these and other applications of shrinkage estimation, the gain in precision from borrowing strength via a shrinkage estimator can be substantial. The confidence intervals for the shrinkage estimates of WIC eligibles in 1992 were, on average, 61 percent narrower than the corresponding direct sample confidence intervals (Schirm 1995). To obtain that same gain in precision with a direct estimator would require nearly a seven-fold increase in sample size, an option that is surely not available to us. Therefore, we must use an indirect estimator and borrow strength.

As noted before, we have used shrinkage estimators to derive state estimates of poverty and food stamp eligibility and participation. These estimators borrow strength across states by combining direct sample and regression estimates. Like the estimators used in the other applications described earlier, our estimators here also borrow strength by using data from outside the main sample survey (the CPS), specifically, data from the decennial census and administrative records systems. Although the shrinkage estimates derived for any one application are not guaranteed to be more accurate than estimates obtained using some other method, shrinkage estimators have good statistical properties in general, and we have found for our specific applications that as in previous applications, shrinkage can greatly improve precision. Additional support for shrinkage estimators is provided by the findings from simulation studies. For example, in a comprehensive evaluation of the relative accuracy of alternative estimators of state poverty rates, Schirm (1994) found that shrinkage estimates are substantially more accurate than direct estimates or indirect estimates obtained from other methods that have been widely used.

II. A STEP-BY-STEP GUIDE TO DERIVING STATE POVERTY ESTIMATES

This chapter describes our procedure for estimating the number of poor people and the poverty rate (the percentage poor) in each state. This procedure, summarized by the flow chart in Figure II.1, has the following five steps:

1. From the Current Population Survey (CPS), calculate sample estimates of state poverty rates.

2. Using a regression model, predict state poverty rates based on (i) National School Lunch Program (NSLP) participation, (ii) Supplemental Security Income (SSI) program participation, and (iii) state poverty rates estimated from the last decennial census.

3. Using "shrinkage" methods, average the sample estimates and regression predictions to obtain preliminary shrinkage estimates of state poverty rates.

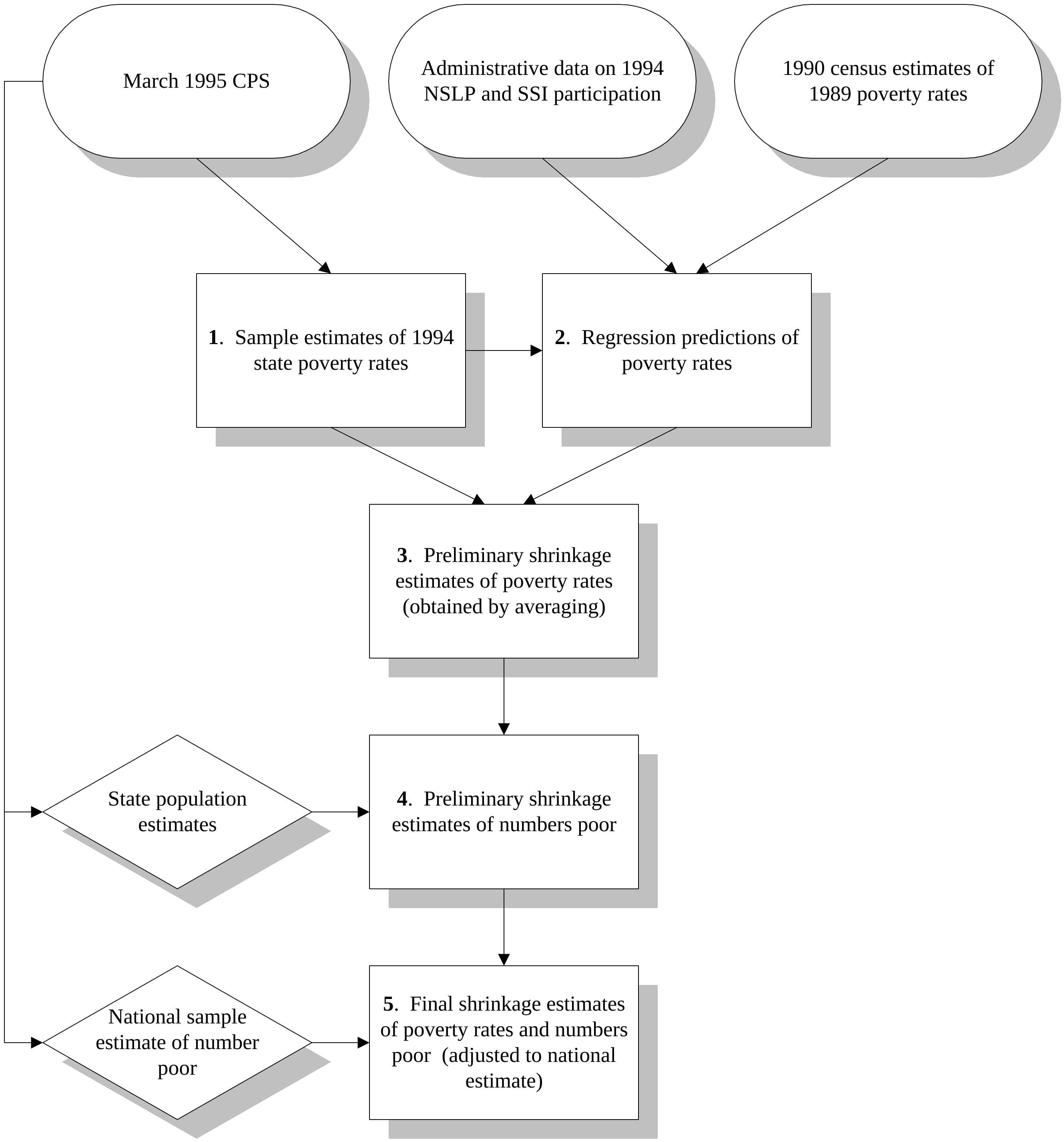
4. For each state, multiply the preliminary shrinkage estimate of the poverty rate by the state population to obtain a preliminary shrinkage estimate of the number poor.

5. Adjust the preliminary state shrinkage estimates of the numbers poor to derive final shrinkage estimates that sum to the national total obtained directly from the CPS.

Each step is described in the remainder of this chapter, and additional technical details are provided in the Appendix. We use the same five-step procedure to derive state estimates of the numbers of people eligible for food stamps and food stamp participation rates, although there are differences between the poverty and food stamp applications in how each step is carried out. These differences are discussed in the Appendix.

FIGURE II.1

THE ESTIMATION PROCEDURE



1. From the CPS, calculate sample estimates of state poverty rates.

Table II.1 displays sample estimates of state poverty rates from the March 1995 CPS. Because the CPS collects family income data for the prior calendar year, the sample estimates pertain to 1994. According to the table, 16.7 percent of all people in Oklahoma, for example, were poor in 1994. A family was poor if its income was below the applicable poverty threshold. In 1994, the poverty threshold for a four-person family with two children was $15,029.

Although relatively simple to calculate, the CPS sample estimates are relatively imprecise. The standard errors for the CPS estimates, reported in the Appendix, tend to be large, so our uncertainty about states' true poverty rates is great. For example, according to widely used statistical standards, we can be confident only that Oklahoma's poverty rate was between 12.8 percent and 20.6 percent. This range is so wide and our uncertainty so great because the CPS sample in Oklahoma is small.

CPS sample estimates of food stamp eligibility and participation are far less simple to derive than estimates of poverty. The main reason is that some critical information needed to determine whether a household is eligible for food stamps, including data on expenses and assets, is not collected in the CPS. The approach used to address these limitations is described in the Appendix.

2. Using a regression model, predict state poverty rates based on (i) National School Lunch Program (NSLP) participation, (ii) Supplemental Security Income (SSI) program participation, and (iii) state poverty rates estimated from the last decennial census.

The main limitation of the sample estimates derived in the previous step is imprecision. Regression can reduce that imprecision. Regression estimates are predictions based on nonsample or highly precise sample data, such as census and administrative records data.

Figure II.2 illustrates how the regression estimator works. The simple example in the figure has just nine states and one predictor variable--NSLP participation--that will be used to predict each

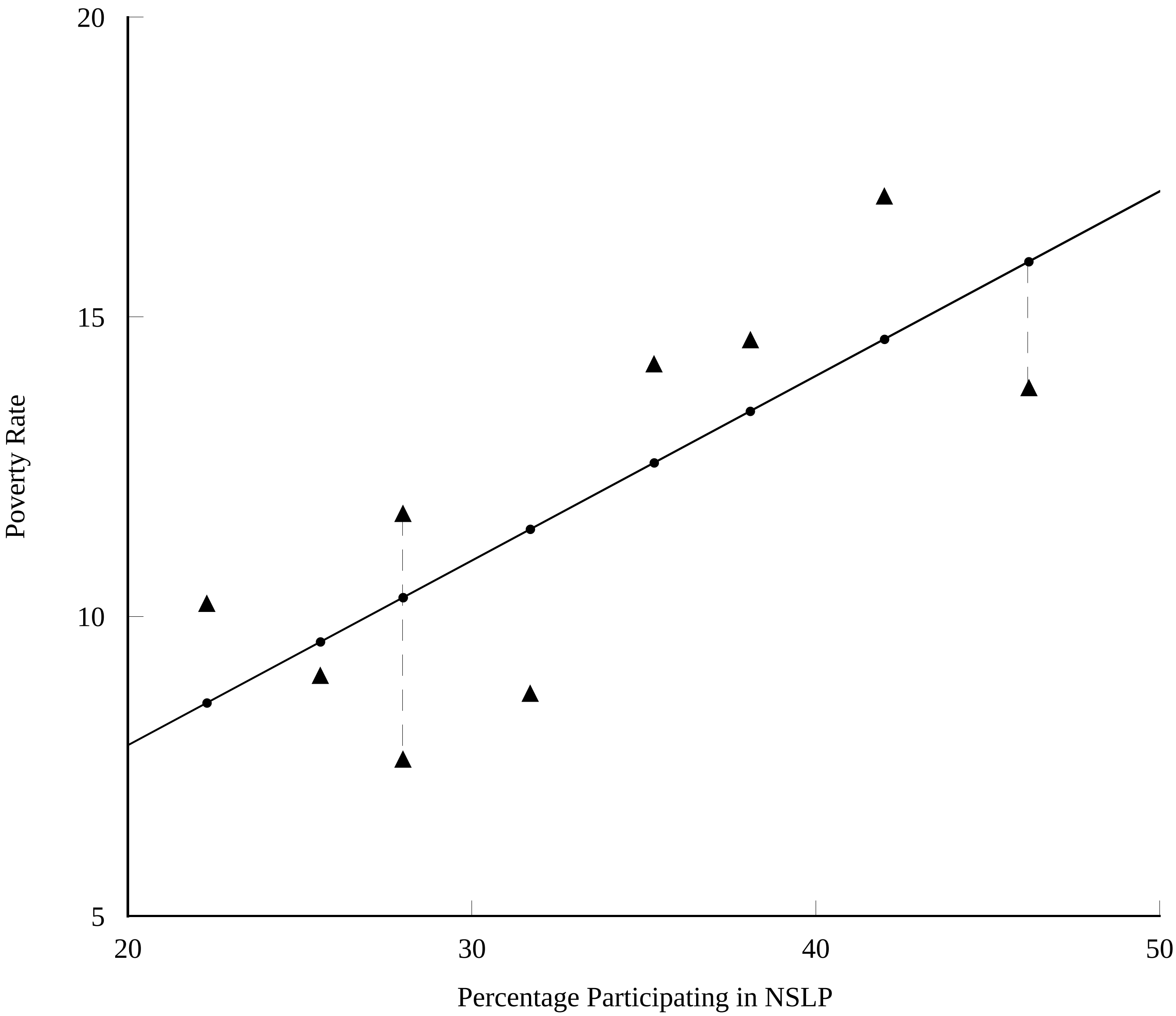
TABLE II.1

1994 POVERTY RATES
(Percent)

State	Sample Estimate	Regression Estimate	Shrinkage Estimate
Alabama	16.4	17.6	17.3
Alaska	10.2	8.9	9.5
Arizona	15.9	14.7	15.2
Arkansas	15.3	17.3	16.4
California	17.9	15.0	16.2
Colorado	9.0	10.6	10.0
Connecticut	10.8	8.4	8.8
Delaware	8.3	10.6	9.5
District of Columbia	21.2	21.6	21.5
Florida	14.9	14.4	14.6
Georgia	14.0	15.4	14.7
Hawaii	8.7	10.8	9.9
Idaho	12.0	12.0	12.0
Illinois	12.4	12.0	12.2
Indiana	13.7	10.2	10.8
Iowa	10.7	10.4	10.5
Kansas	14.9	11.5	12.6
Kentucky	18.5	17.7	17.8
Louisiana	25.7	21.6	22.6
Maine	9.4	11.5	10.4
Maryland	10.7	10.0	10.3
Massachusetts	9.7	10.2	9.9
Michigan	14.1	11.9	13.3
Minnesota	11.7	9.8	10.4
Mississippi	19.9	23.3	22.6
Missouri	15.6	12.4	12.8
Montana	11.5	12.3	12.1
Nebraska	8.8	10.5	9.7
Nevada	11.1	10.0	10.3
New Hampshire	7.7	6.9	7.3
New Jersey	9.2	9.7	9.6
New Mexico	21.1	21.3	21.3
New York	17.0	15.2	16.1
North Carolina	14.2	13.6	14.0
North Dakota	10.4	11.4	10.6
Ohio	14.1	11.4	12.5
Oklahoma	16.7	15.7	15.9
Oregon	11.8	11.3	11.5
Pennsylvania	12.5	11.1	12.2
Rhode Island	10.2	11.3	10.9
South Carolina	13.8	16.7	15.9
South Dakota	14.5	13.7	13.8
Tennessee	14.6	15.4	15.0
Texas	19.1	17.1	17.4
Utah	8.0	10.5	8.9
Vermont	7.6	11.0	9.8
Virginia	10.7	10.7	10.7
Washington	11.7	10.9	11.3
West Virginia	18.6	18.1	18.2
Wisconsin	9.0	10.2	9.7
Wyoming	9.3	10.9	9.9

FIGURE II.2

AN ILLUSTRATIVE REGRESSION ESTIMATOR



state's poverty rate. NSLP participation is measured by the percentage of school-aged children approved to receive free or reduced-price lunches. The triangles in the figure correspond to sample estimates; a triangle shows NSLP participation in a state (read off the horizontal axis) and the sample estimate of the poverty rate in that state (read off the vertical axis). Not surprisingly, the graph suggests that NSLP participation is systematically associated with the poverty rate. States with higher percentages of school-aged children participating in the NSLP tend to have higher poverty rates, although the relationship is far from perfect. To measure this relationship between NSLP participation and poverty, we can use a technique called "least squares regression" to draw a line through the triangles (that is, we "regress" the sample estimates on the predictor variable). Regression estimates of poverty rates are points on that line, the circles in Figure II.2. The predicted poverty rate for a particular state is obtained by moving up or down from the state's sample estimate (the triangle) to the regression line (where there is a circle) and reading the value off the vertical axis. For example, the regression estimator predicts a poverty rate of about 10 percent for both states with just under 30 percent of children participating in the NSLP. In contrast, for the state with about 45 percent of children participating in the NSLP, the predicted poverty rate is nearly 16 percent.

Table II.1 displays the sample estimates calculated in Step 1 and the regression estimates calculated in this step. To derive the regression estimates in the table, we included all of the states, not just nine as in our illustrative example, and we used three predictor variables, not just one. Adding two predictor variables improves our predictions. The three predictor variables used measure (1) NSLP participation in 1994, (2) SSI participation in 1994, and (3) the poverty rate in 1989. The first two predictors were obtained from administrative records data, and the third was calculated from the 1990 decennial census, which, like the CPS, collects family income data for the prior calendar year (1989). These three predictors were selected as the best from a longer list presented in the

Appendix, which presents the set of best predictors for the food stamp eligibility regression and also provides complete definitions for all of the best predictors. As expected, the estimated regression for poverty rates, which is displayed in the Appendix, shows that states with higher NSLP and SSI participation and higher poverty rates in the past tend to have higher current poverty rates. The Appendix also presents standard errors for the regression estimates. These tend to be fairly equal across the states and much smaller than the largest standard errors for sample estimates, reflecting substantial gains in precision from regression for the states with the most error-prone sample estimates.

Comparing how the sample and regression estimators use data reveals how the regression estimator "borrows strength" to improve precision. When we derived sample estimates in Step 1, we used only CPS sample data from Oklahoma to estimate Oklahoma's poverty rate, even though Oklahoma, like most states, has a fairly small CPS sample. Deriving regression estimates in this step, we estimated a regression line from sample, administrative, and census data for all the states and used the estimated line (with administrative and census data for Oklahoma) to predict Oklahoma's poverty rate. In other words, the regression estimator not only uses the sample estimates from every state to develop a regression estimate for a single state but also incorporates data from outside the sample, namely, data in administrative records systems and the census.

The regression estimator improves precision by using more data. It uses that additional data to identify states with sample estimates that seem too high or too low because of sampling error, that is, error from drawing a sample--a subset of the population--that has a higher or lower poverty rate than the entire state population has. For example, suppose a state had low NSLP and SSI participation in 1994 and a low poverty rate in 1989. Our regression estimator would predict a low poverty rate for 1994, implying that a sample estimate showing a high poverty rate is probably too high. On the other hand, a sample estimate showing a low poverty rate is probably too low if NSLP and SSI participation in 1994 and the poverty rate in 1989 were high.

3. Using "shrinkage" methods, average the sample estimates and regression predictions to obtain preliminary shrinkage estimates of state poverty rates.

As noted, the limitation of the sample estimator is imprecision. The limitation of the regression estimator is called "bias." Some states really have higher or lower poverty rates than we expect (and predict with the regression estimator) based on NSLP and SSI participation and 1989 poverty rates. Such errors in regression estimates reflect bias.

These limitations arise for the following reasons. The sample estimator uses only sample data for one state to obtain an estimate for that state. It does not use sample data for other states or administrative records or census data. Although the regression estimator borrows strength, using data from all the states and administrative and census data, it makes no further use of the sample data after estimating the regression line. It treats the entire difference between the sample and regression estimates as sampling error, that is, error in the sample estimate. No allowance is made for prediction error, that is, error in the regression estimate. Although not all, if any, true state poverty rates lie on the regression line, the regression estimator assumes they do.

Using all of the information at hand, a shrinkage estimator addresses the limitations of the sample and regression estimators by combining the sample and regression estimates, striking a compromise. As illustrated in Figure II.3, a shrinkage estimator takes a weighted average of the sample and regression estimates. Generally, the more precise the sample estimate for a state, the closer the shrinkage estimate will be to it. The larger samples drawn in large states support more precise sample estimates, so shrinkage estimates tend to be closer to the sample estimates for large states. Given the precision of the sample estimate for a state, the weight given to the regression

FIGURE II.3

SHRINKAGE ESTIMATION

Poor predictions or state with relatively large sample ⇒ more weight on sample estimate:

●----------------------●--●

sample estimate	shrinkage estimate	regression estimate

Good predictions or state with relatively small sample ⇒ more weight on regression estimate:

●--●----------------------●

sample estimate	shrinkage estimate	regression estimate

estimate depends on how well the regression line "fits." If we could not find good predictors reflecting why some states have higher poverty rates than other states, we say that the regression line "fits poorly." The shrinkage estimate will be farther from the regression estimate and closer to the sample estimate when the regression line fits poorly. In contrast, the shrinkage estimate will be closer to the regression estimate and farther from the sample estimate when the regression line fits well. Striking a compromise between the sample and regression estimators, the shrinkage estimator strikes a compromise between imprecision and bias. The sample and regression estimates are optimally weighted to improve accuracy by minimizing a measure of error that reflects both imprecision and bias. By accepting a little bias, the shrinkage estimator may be substantially more precise than the sample estimator. By sacrificing a little precision, the shrinkage estimator may be substantially less biased than the regression estimator.

Table II.1 presents shrinkage estimates of 1994 state poverty rates. Table II.1 also displays the sample and regression estimates from Steps 1 and 2. Because we will want to adjust our shrinkage estimates later to make them consistent with national sample totals, the shrinkage estimates derived in this step are designated as "preliminary."

4. For each state, multiply the preliminary shrinkage estimate of the poverty rate by the state population to obtain a preliminary shrinkage estimate of the number poor.

To obtain estimated numbers from estimated rates (that is, percentages), we require state population totals. The population totals we used were estimated directly from the CPS.

Table II.2 displays preliminary shrinkage estimates of the numbers of poor people in 1994. It also shows shrinkage estimates of poverty rates from Step 3 and state population estimates from the CPS. According to the table, there were 3,232,010 people living in Oklahoma. Our shrinkage

TABLE II.2

PRELIMINARY SHRINKAGE ESTIMATES OF THE
NUMBERS OF POOR PEOPLE IN 1994

State	Preliminary Shrinkage Estimate of Poverty Rate (Percent)	Population	Preliminary Shrinkage Estimate of Number Poor
Alabama	17.263	4,298,948	742,127
Alaska	9.547	591,663	56,486
Arizona	15.220	4,223,399	642,801
Arkansas	16.421	2,414,045	396,410
California	16.211	31,668,636	5,133,803
Colorado	9.963	3,735,578	372,176
Connecticut	8.789	3,192,034	280,548
Delaware	9.522	680,852	64,831
District of Columbia	21.497	606,654	130,412
Florida	14.639	14,257,715	2,087,187
Georgia	14.675	7,219,951	1,059,528
Hawaii	9.905	1,106,273	109,576
Idaho	12.000	1,138,038	136,565
Illinois	12.232	11,808,353	1,444,398
Indiana	10.818	5,967,451	645,559
Iowa	10.488	2,815,025	295,240
Kansas	12.604	2,521,841	317,853
Kentucky	17.846	3,843,077	685,836
Louisiana	22.561	4,351,021	981,634
Maine	10.412	1,200,874	125,035
Maryland	10.319	5,044,669	520,559
Massachusetts	9.930	6,004,629	596,260
Michigan	13.264	9,519,225	1,262,630
Minnesota	10.440	4,486,070	468,346
Mississippi	22.628	2,586,954	585,376
Missouri	12.803	5,106,974	653,846
Montana	12.123	843,915	102,308
Nebraska	9.723	1,647,545	160,191
Nevada	10.318	1,520,748	156,911
New Hampshire	7.309	1,130,744	82,646
New Jersey	9.563	7,920,069	757,396
New Mexico	21.275	1,684,566	358,391
New York	16.071	18,212,732	2,926,968
North Carolina	13.987	6,895,266	964,441
North Dakota	10.568	626,983	66,260
Ohio	12.452	11,139,219	1,387,056
Oklahoma	15.922	3,232,010	514,601
Oregon	11.468	3,152,358	361,512
Pennsylvania	12.178	11,966,650	1,457,299
Rhode Island	10.883	968,337	105,384
South Carolina	15.917	3,633,217	578,299
South Dakota	13.835	736,994	101,963
Tennessee	15.002	5,337,792	800,776
Texas	17.357	18,894,375	3,279,497
Utah	8.881	1,925,720	171,023
Vermont	9.827	589,172	57,898
Virginia	10.713	6,615,866	708,758
Washington	11.272	5,258,594	592,749
West Virginia	18.201	1,804,431	328,424
Wisconsin	9.654	5,003,466	483,035
Wyoming	9.933	485,403	48,215
United States		261,616,121	36,347,019

estimate is that 15.922 percent of them were poor. Therefore, our preliminary shrinkage estimate of the number poor is (15.922 ÷ 100) × 3,232,010 = 514,601 people.

5. Adjust the preliminary state shrinkage estimates of the numbers poor to derive final shrinkage estimates that sum to the national total obtained directly from the CPS.

The preliminary state shrinkage estimates derived in Step 4 sum to 36,347,019 poor people nationwide. According to the March 1995 CPS, there were 38,059,118 poor people in the entire United States. To obtain final shrinkage estimates of state poverty counts that sum (aside from rounding error) to the national total from the CPS, which is the official figure for the United States, we multiply each of the preliminary state shrinkage estimates by 38,059,118 ÷ 36,347,019 (≈ 1.0471). Such benchmarking of estimates for smaller areas to a relatively precise estimated total for a larger area is common practice. To obtain final shrinkage estimates of poverty rates, we divided the final shrinkage estimates of poverty counts by the state population totals used in the previous step. All final estimates, including those for food stamp eligibility counts and participation rates, are presented in the next chapter. As described in the Appendix, the food stamp estimates are adjusted to a national sample total from the Survey of Income and Program Participation (SIPP), rather than the CPS.

III. STATE ESTIMATES OF POVERTY, FSP ELIGIBILITY, AND FSP PARTICIPATION FOR 1994

Table III.1 presents our final shrinkage estimates of the number of poor people and the poverty rate in each state in 1994. As documented in the Appendix, the shrinkage estimates are relatively precise; they have much smaller standard errors and narrower confidence intervals than the CPS sample estimates. Table III.2 displays approximate 90-percent confidence intervals showing the uncertainty remaining after using shrinkage estimation. One interpretation of such an interval is that there is a 90 percent chance that the true value--that is, the true number of poor people or the true poverty rate--falls within the estimated bounds. For example, while our best estimate is that Oklahoma's poverty rate was 16.7 percent in 1994 (see Table III.1), the true rate may have been higher or lower. However, the chances are 90 in 100 that the true rate was between 14.7 and 18.7 percent, a reasonably narrow interval that is only about half as wide as the interval (cited in Chapter II) around the direct sample estimate. A narrower interval means that we are less uncertain about the true value. According to our calculations, a shrinkage confidence interval for a poverty rate is, on average, only about 70 percent as wide as the corresponding sample confidence interval. Thus, shrinkage substantially improves precision and reduces our uncertainty.

Table III.3 displays final shrinkage estimates of the number of people eligible for food stamps and the food stamp participation rate in each state in January 1994. Table III.4 presents approximate 90-percent confidence intervals for these estimates. Like the shrinkage estimates for poverty rates, the shrinkage estimates for food stamp participation rates are much more precise than CPS sample estimates, with shrinkage confidence intervals being only about 64 percent as wide as sample confidence intervals, on average. Despite the impressive gains in precision, substantial uncertainty about the true participation rates for some states remains even after the application of shrinkage

TABLE III.1

FINAL SHRINKAGE ESTIMATES OF THE NUMBERS OF
POOR PEOPLE AND POVERTY RATES IN 1994

State	Number of Poor People	Poverty Rate (Percent)
Alabama	777,085	18.1
Alaska	59,147	10.0
Arizona	673,080	15.9
Arkansas	415,083	17.2
California	5,375,626	17.0
Colorado	389,707	10.4
Connecticut	293,763	9.2
Delaware	67,885	10.0
District of Columbia	136,555	22.5
Florida	2,185,502	15.3
Georgia	1,109,436	15.4
Hawaii	114,738	10.4
Idaho	142,997	12.6
Illinois	1,512,435	12.8
Indiana	675,967	11.3
Iowa	309,147	11.0
Kansas	332,825	13.2
Kentucky	718,141	18.7
Louisiana	1,027,873	23.6
Maine	130,925	10.9
Maryland	545,080	10.8
Massachusetts	624,346	10.4
Michigan	1,322,105	13.9
Minnesota	490,407	10.9
Mississippi	612,950	23.7
Missouri	684,645	13.4
Montana	107,127	12.7
Nebraska	167,736	10.2
Nevada	164,302	10.8
New Hampshire	86,539	7.7
New Jersey	793,073	10.0
New Mexico	375,273	22.3
New York	3,064,841	16.8
North Carolina	1,009,870	14.6
North Dakota	69,381	11.1
Ohio	1,452,392	13.0
Oklahoma	538,841	16.7
Oregon	378,541	12.0
Pennsylvania	1,525,944	12.8
Rhode Island	110,348	11.4
South Carolina	605,539	16.7
South Dakota	106,766	14.5
Tennessee	838,495	15.7
Texas	3,433,975	18.2
Utah	179,079	9.3
Vermont	60,625	10.3
Virginia	742,143	11.2
Washington	620,670	11.8
West Virginia	343,895	19.1
Wisconsin	505,788	10.1
Wyoming	50,486	10.4
United States	38,059,119	14.5

TABLE III.2

APPROXIMATE 90-PERCENT CONFIDENCE INTERVALS
FOR SHRINKAGE ESTIMATES OF POVERTY

	Number of Poor People		Poverty Rate (Percent)	
State	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Alabama	694,447	859,723	16.2	20.0
Alaska	50,484	67,810	8.5	11.5
Arizona	603,097	743,063	14.3	17.6
Arkansas	374,125	456,041	15.5	18.9
California	4,836,684	5,914,568	15.3	18.7
Colorado	328,386	451,028	8.8	12.1
Connecticut	229,214	358,312	7.2	11.2
Delaware	57,143	78,627	8.4	11.5
District of Columbia	120,431	152,679	19.9	25.2
Florida	1,960,299	2,410,705	13.7	16.9
Georgia	1,006,091	1,212,781	13.9	16.8
Hawaii	96,712	132,764	8.7	12.0
Idaho	122,944	163,050	10.8	14.3
Illinois	1,365,989	1,658,881	11.6	14.0
Indiana	558,582	793,352	9.4	13.3
Iowa	259,398	358,896	9.2	12.7
Kansas	286,607	379,043	11.4	15.0
Kentucky	636,057	800,225	16.6	20.8
Louisiana	931,418	1,124,328	21.4	25.8
Maine	113,281	148,569	9.4	12.4
Maryland	464,008	626,152	9.2	12.4
Massachusetts	541,603	707,089	9.0	11.8
Michigan	1,196,670	1,447,540	12.6	15.2
Minnesota	413,367	567,447	9.2	12.6
Mississippi	549,853	676,047	21.3	26.1
Missouri	582,779	786,511	11.4	15.4
Montana	90,643	123,611	10.7	14.6
Nebraska	142,621	192,851	8.7	11.7
Nevada	136,876	191,728	9.0	12 6
New Hampshire	70,217	102,861	6.2	9.1
New Jersey	658,288	927,858	8.3	11.7
New Mexico	328,905	421,641	19.5	25.0
New York	2,782,500	3,347,182	15.3	18.4
North Carolina	930,057	1,089,683	13.5	15.8
North Dakota	64,132	74,630	10.2	11.9
Ohio	1,263,974	1,640,810	11.3	14.7
Oklahoma	474,597	603,085	14.7	18.7
Oregon	323,482	433,600	10.3	13.8
Pennsylvania	1,411,339	1,640,549	11.8	13.7
Rhode Island	94,436	126,260	9.8	13.0
South Carolina	535,760	675,318	14.7	18.6
South Dakota	91,837	121,695	12.5	16.5
Tennessee	760,252	916,738	14.2	17.2
Texas	3,008,608	3,859,342	15.9	20.4
Utah	154,666	203,492	8.0	10.6
Vermont	50,000	71,250	8.5	12.1
Virginia	668,527	815,759	10.1	12.3
Washington	543,316	698,024	10.3	13.3
West Virginia	307,872	379,918	17.1	21.1
Wisconsin	428,050	583,526	8.6	11.7
Wyoming	44,274	56,698	9.1	11.7

TABLE III.3

FINAL SHRINKAGE ESTIMATES OF THE NUMBERS OF PEOPLE ELIGIBLE FOR FOOD STAMPS AND FOOD STAMP PARTICIPATION RATES IN JANUARY 1994

State	Number of Eligible People	Participation Rate (Percent)
Alabama	709,166	77.3
Alaska	70,393	37.6
Arizona	626,508	77.5
Arkansas	370,445	77.5
California	5,498,575	57.1
Colorado	364,055	72.9
Connecticut	328,883	65.9
Delaware	66,849	87.8
District of Columbia	144,721	59.2
Florida	2,202,155	65.2
Georgia	1,143,607	70.1
Hawaii	123,070	89.6
Idaho	119,900	66.9
Illinois	1,670,469	70.0
Indiana	640,036	78.4
Iowa	254,895	75.2
Kansas	287,093	65.2
Kentucky	678,141	77.4
Louisiana	1,001,920	75.7
Maine	134,637	100.0
Maryland	558,582	66.9
Massachusetts	636,051	68.4
Michigan	1,266,521	79.9
Minnesota	433,318	72.4
Mississippi	611,759	82.6
Missouri	685,035	84.4
Montana	91,632	77.6
Nebraska	135,976	78.6
Nevada	151,150	63.2
New Hampshire	89,432	65.7
New Jersey	844,269	63.0
New Mexico	338,661	70.8
New York	2,968,636	70.3
North Carolina	984,479	63.4
North Dakota	65,507	70.0
Ohio	1,529,558	79.4
Oklahoma	484,519	75.5
Oregon	342,274	80.1
Pennsylvania	1,429,099	81.6
Rhode Island	103,069	89.6
South Carolina	568,672	68.1
South Dakota	87,168	62.3
Tennessee	915,615	79.9
Texas	3,748,820	70.3
Utah	169,763	74.2
Vermont	74,068	100.0
Virginia	671,043	76.8
Washington	603,250	74.3
West Virginia	327,389	94.8
Wisconsin	467,975	69.9
Wyoming	46,864	70.1
United States	37,865,672	70.9

TABLE III.4

APPROXIMATE 90-PERCENT CONFIDENCE INTERVALS FOR SHRINKAGE ESTIMATES OF FOOD STAMP ELIGIBILITY AND PARTICIPATION

State	Number of Eligible People		Participation Rate (Percent)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Alabama	634,714	783,618	69.2	85.4
Alaska	56,128	84,658	30.0	45.2
Arizona	577,100	675,916	71.4	83.7
Arkansas	335,867	405,023	70.3	84.7
California	5,245,288	5,751,862	54.5	59.8
Colorado	322,180	405,930	64.5	81.3
Connecticut	273,708	384,058	54.9	77.0
Delaware	57,638	76,060	75.7	99.9
District of Columbia	125,694	163,748	51.4	67.0
Florida	2,039,173	2,365,137	60.4	70.0
Georgia	1,062,932	1,224,282	65.2	75.0
Hawaii	103,397	142,743	75.3	100.0
Idaho	105,681	134,119	58.9	74.8
Illinois	1,524,830	1,816,108	63.9	76.1
Indiana	552,073	727,999	67.6	89.2
Iowa	217,660	292,130	64.2	86.2
Kansas	251,645	322,541	57.1	73.2
Kentucky	623,134	733,148	71.1	83.7
Louisiana	932,516	1,071,324	70.5	80.9
Maine	122,424	146,850	90.9	100.0
Maryland	488,993	628,171	58.6	75.3
Massachusetts	577,686	694,416	62.1	74.7
Michigan	1,160,209	1,372,833	73.2	86.6
Minnesota	375,786	490,850	62.8	82.0
Mississippi	566,960	656,558	76.5	88.6
Missouri	613,788	756,282	75.6	93.2
Montana	80,664	102,600	68.4	86.9
Nebraska	118,701	153,251	68.6	88.6
Nevada	129,535	172,765	54.2	72.2
New Hampshire	74,256	104,608	54.6	76.9
New Jersey	763,241	925,297	56.9	69.0
New Mexico	318,119	359,203	66.5	75.1
New York	2,803,175	3,134,097	66.4	74.2
North Carolina	911,924	1,057,034	58.7	68.1
North Dakota	57,573	73,441	61.6	78.5
Ohio	1,398,037	1,661,079	72.5	86.2
Oklahoma	441,318	527,720	68.8	82.3
Oregon	298,645	385,903	69.9	90.3
Pennsylvania	1,335,789	1,522,409	76.2	86.9
Rhode Island	89,118	117,020	77.5	100.0
South Carolina	512,612	624,732	61.4	74.8
South Dakota	75,367	98,969	53.9	70.8
Tennessee	851,525	979,705	74.3	85.5
Texas	3,619,858	3,877,782	67.8	72.7
Utah	146,362	193,164	63.9	84.4
Vermont	65,924	82,212	89.0	100.0
Virginia	601,780	740,306	68.9	84.7
Washington	546,895	659,605	67.4	81.3
West Virginia	306,251	348,527	88.7	100.0
Wisconsin	409,374	526,576	61.2	78.7
Wyoming	41,365	52,363	61.8	78.3

methods. Nevertheless, as discussed in Schirm (1998), the shrinkage estimates are sufficiently precise to show, for example, whether a state's food stamp participation rate probably fell at the top, at the bottom, or in the middle of the distribution. That would be enough information for many important purposes, such as guiding an initiative to improve program performance.

REFERENCES

Cody, Scott, and Carole Trippe. "Trends in FSP Participation Rates: Focus on August 1995." Washington, DC: Mathematica Policy Research, Inc., October 1997.

Fay, Robert E., and Roger Herriott. "Estimates of Incomes for Small-Places: An Application of James-Stein Procedures to Census Data." *Journal of the American Statistical Association,* vol. 74, no. 366, June 1979, pp. 269-277.

Fay, Robert E., Charles T. Nelson, and Leon Litow. "Estimation of Median Income for 4-Person Families by State." In *Indirect Estimators in Federal Programs*. Statistical Policy Working Paper no. 21. Washington, DC: Office of Management and Budget, July 1993.

National Research Council, Committee on National Statistics, Panel on Estimates of Poverty for Small Geographic Areas. *Small-Area Estimates of School-Age Children in Poverty, Interim Report 2, Evaluation of Revised 1993 County Estimates for Title I Allocations*, edited by Constance F. Citro, Michael L. Cohen, and Graham Kalton. Washington, DC: National Academy Press, 1998.

Rao, J.N.K., C.F.J. Wu, and K. Yue. "Some Recent Work on Resampling Methods for Complex Surveys." *Survey Methodology*, vol. 18, no. 2, December 1992, pp. 209-217.

Schirm, Allen L. "Reaching Those in Need: How Effective is the Food Stamp Program?" Washington, DC: Mathematica Policy Research, Inc., 1998.

Schirm, Allen L. "Borrowing Strength Across Space and Time: Bayesian Shrinkage Estimates of Infants and Children Income Eligible for the WIC Program in 1994, by State." Washington, DC: Mathematica Policy Research, Inc., September 1996.

Schirm, Allen L. "State Estimates of Infants and Children Income Eligible for the WIC Program in 1992." Washington, DC: Mathematica Policy Research, Inc., May 1995.

Schirm, Allen L. "The Relative Accuracy of Direct and Indirect Estimators of State Poverty Rates." *1994 Proceedings of the Section on Survey Research Methods*. Alexandria, VA: American Statistical Association, 1994.

Trippe, Carole. "Trends in FSP Participation Rates: Focus on August 1994." Washington, DC: Mathematica Policy Research, Inc., September 1996.

U.S. Department of Commerce, Bureau of the Census. "Income, Poverty, and Valuation of Noncash Benefits: 1994." *Current Population Reports*, series P60, no. 189. Washington, DC: U.S. Government Printing Office, April 1996.

U.S. Department of Commerce, Bureau of the Census. "Poverty in the United States--Changes Between the Censuses." *Statistical Brief*, no. SB/93-15. Washington, DC: U.S. Bureau of the Census, August 1993.

U.S. Department of Commerce, Bureau of Economic Analysis. *Survey of Current Business*, vol. 76, no. 10. Washington, DC: U.S. Bureau of Economic Analysis, October 1996.

U.S. House of Representatives, Committee on Ways and Means. *1994 Green Book*. Washington, DC: U.S. Government Printing Office, July 1994.

APPENDIX A

THE ESTIMATION PROCEDURE: ADDITIONAL TECHNICAL DETAILS

This appendix provides additional information and technical details about our five-step procedure to estimate the number of poor people and the poverty rate in each state. Although this same basic procedure was also used to estimate the numbers of people eligible for food stamps and food stamp participation rates, there are some differences in how each step was carried out. These differences are discussed in this appendix. The procedure for estimating the numbers of people eligible for food stamps and food stamp participation rates, summarized by the flow chart in Figure A.1, has the following five steps:

1. From the Current Population Survey (CPS), calculate sample estimate of percentage eligible for food stamps in each state.

2. Using a regression model, predict state food stamp eligibility percentages based on administrative and decennial census data.

3. Using "shrinkage" methods, average the sample estimates and regression predictions to obtain preliminary shrinkage estimates of state food stamp eligibility percentages.

4. For each state, multiply the preliminary shrinkage estimate of the percentage eligible by the state population to obtain a preliminary shrinkage estimate of the number eligible.

5. Adjust the preliminary state shrinkage estimates of the numbers eligible to derive final shrinkage estimates that sum to the national total obtained directly from the Survey of Income and Program Participation (SIPP).

An analogous list of steps for estimating poverty counts and rates was presented in the main text with a figure similar to Figure A.1.

1. From the CPS, calculate sample estimates of poverty rate and percentage eligible for food stamps in each state.

Table A.1 displays CPS direct sample estimates of state poverty rates. We calculated these poverty rates using the same method used by the Census Bureau, which entails comparing a CPS

FIGURE A.1

THE ESTIMATION PROCEDURE

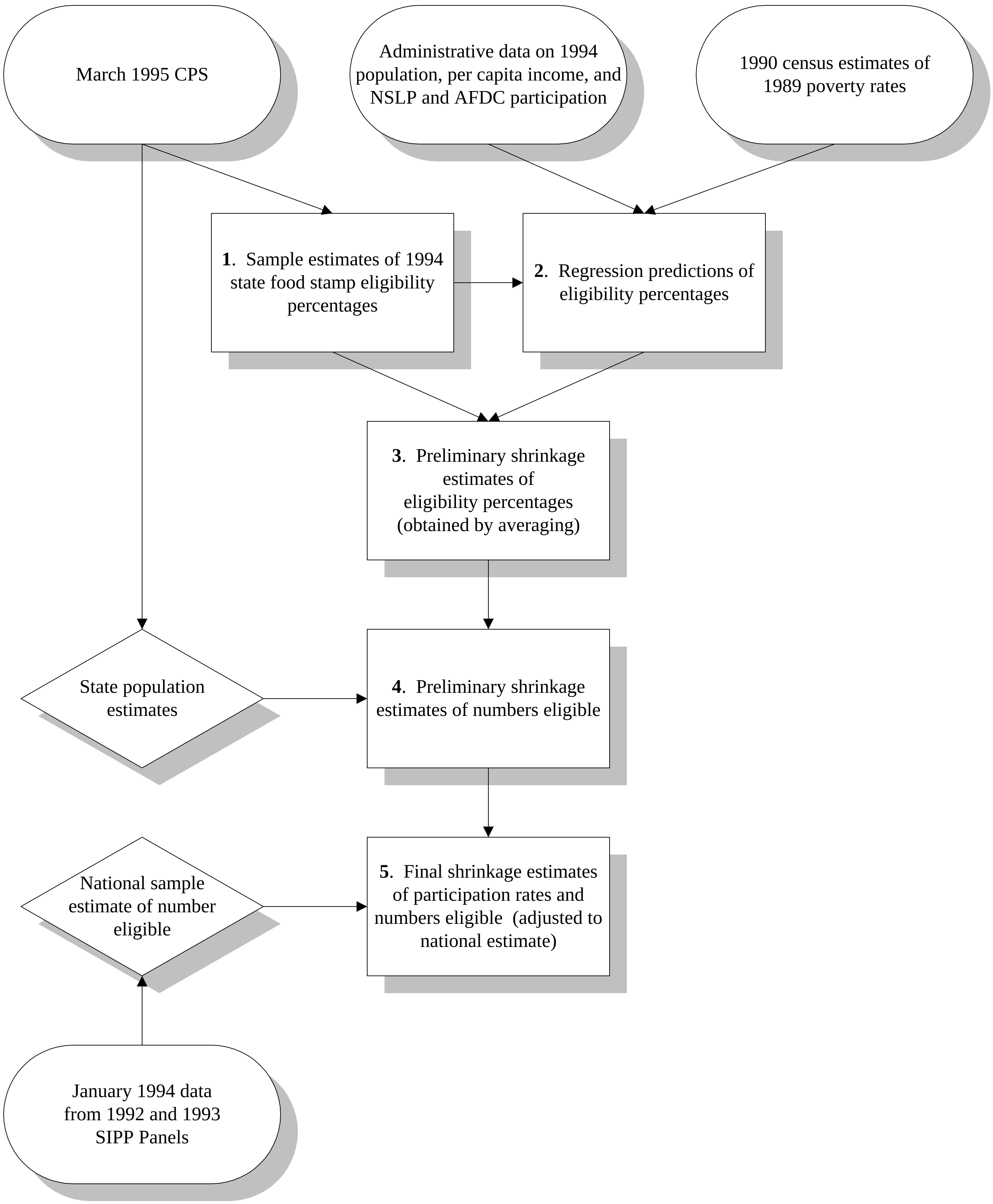


TABLE A.1

POVERTY RATES IN 1994

	Point Estimate			Standard Error		
State	Sample	Regression	Shrinkage	Sample	Regression	Shrinkage
Alabama	16.4	17.6	17.3	2.0	1.4	1.1
Alaska	10.2	8.9	9.5	1.1	1.3	0.9
Arizona	15.9	14.7	15.2	1.3	1.4	1.0
Arkansas	15.3	17.3	16.4	1.3	1.4	1.0
California	17.9	15.0	16.2	1.4	1.4	1.0
Colorado	9.0	10.6	10.0	1.5	1.3	1.0
Connecticut	10.8	8.4	8.8	2.7	1.3	1.2
Delaware	8.3	10.6	9.5	1.2	1.3	0.9
District of Columbia	21.2	21.6	21.5	2.4	1.8	1.5
Florida	14.9	14.4	14.6	1.3	1.3	0.9
Georgia	14.0	15.4	14.7	1.1	1.3	0.8
Hawaii	8.7	10.8	9.9	1.3	1.3	0.9
Idaho	12.0	12.0	12.0	1.8	1.3	1.0
Illinois	12.4	12.0	12.2	0.9	1.2	0.7
Indiana	13.7	10.2	10.8	2.6	1.3	1.1
Iowa	10.7	10.4	10.5	1.8	1.3	1.0
Kansas	14.9	11.5	12.6	1.6	1.3	1.1
Kentucky	18.5	17.7	17.8	2.6	1.4	1.2
Louisiana	25.7	21.6	22.6	2.1	1.5	1.3
Maine	9.4	11.5	10.4	1.1	1.3	0.9
Maryland	10.7	10.1	10.3	1.4	1.3	0.9
Massachusetts	9.7	10.2	9.9	1.0	1.4	0.8
Michigan	14.1	11.9	13.3	0.9	1.3	0.8
Minnesota	11.7	9.8	10.4	1.6	1.3	1.0
Mississippi	19.9	23.3	22.6	2.4	1.6	1.4
Missouri	15.6	12.4	12.8	3.0	1.3	1.2
Montana	11.5	12.3	12.1	2.0	1.4	1.1
Nebraska	8.8	10.5	9.7	1.3	1.3	0.9
Nevada	11.1	10.1	10.3	2.0	1.3	1.0
New Hampshire	7.7	6.9	7.3	1.1	1.3	0.8
New Jersey	9.2	9.7	9.6	1.6	1.3	1.0
New Mexico	21.1	21.3	21.3	3.2	1.8	1.6
New York	17.0	15.2	16.1	1.2	1.3	0.9
North Carolina	14.2	13.6	14.0	0.8	1.3	0.7
North Dakota	10.4	11.4	10.6	0.5	1.4	0.5
Ohio	14.1	11.4	12.5	1.4	1.3	1.0
Oklahoma	16.7	15.7	15.9	2.4	1.3	1.2
Oregon	11.8	11.3	11.5	1.8	1.3	1.0
Pennsylvania	12.5	11.1	12.2	0.6	1.3	0.6
Rhode Island	10.3	11.3	10.9	1.4	1.3	1.0
South Carolina	13.8	16.7	15.9	2.0	1.3	1.1
South Dakota	14.5	13.7	13.8	2.7	1.3	1.2
Tennessee	14.6	15.4	15.0	1.1	1.3	0.9
Texas	19.1	17.1	17.4	3.0	1.4	1.3
Utah	8.0	10.5	8.9	0.8	1.3	0.7
Vermont	7.6	11.0	9.8	1.6	1.3	1.0
Virginia	10.7	10.7	10.7	0.8	1.3	0.6
Washington	11.7	10.9	11.3	1.2	1.2	0.9
West Virginia	18.6	18.1	18.2	2.3	1.4	1.2
Wisconsin	9.0	10.2	9.7	1.3	1.3	0.9
Wyoming	9.3	10.9	9.9	0.9	1.3	0.7

family's income to the applicable poverty threshold for that family. Table A.1 also shows standard errors for the sample estimates. The method for obtaining these standard errors is described later.

In addition to poverty estimates, we calculated food stamp eligibility estimates for states by applying food stamp program rules to CPS households. However, as we noted in the main text, food stamp eligibility estimates are more difficult to obtain than poverty estimates because some key information needed to determine whether a household is eligible for food stamps is not collected in the CPS. For example, there are no data on asset balances or expenses deductible from gross income. Also, it is not possible to ascertain directly which members of a dwelling unit purchase and prepare food together. Yet another limitation is that only annual, rather than monthly, income amounts are recorded.

Methods have been developed to successfully address these data limitations. These methods--including procedures for identifying the members of the food stamp household within the (potentially) larger CPS household, distributing annual amounts across months, and imputing net income--are described in Cody and Trippe (1997) and earlier reports in that series.[1]

One new method that was first developed for deriving the state estimates in this report pertains to the imputation of asset information. In previous analyses of trends in national food stamp participation rates (see, for example, Trippe 1996), countable asset balances were imputed by dividing financial asset income reported in the CPS by 0.065 (in other words, assuming that the rate of return on financial assets is 6.5 percent and households have no vehicle assets). This approach typically led to too many households passing the food stamp asset test, too many eligibles overall, and, therefore, low participation rates compared with estimates calculated from the SIPP, which collects detailed

[1]These reports also describe how we applied the food stamp gross and net income tests and calculated the benefits for which an eligible household would qualify.

data on assets.[2] In addition to our concern that a 6.5 percent rate of return is too high, we were concerned that asset balances simply cannot be estimated very well from the information available in the CPS. Thus, we sought to develop a new method.

The basic idea of our new approach to imputing asset information is to improve our prospects for success by seeking only what we need. For estimating the number of eligibles, we do not need to know each household's asset balances. Instead, we need only know whether a household passes the asset test. Indeed, as we will discuss shortly, we need only know the probability that a household passes the asset test. As we expected, we have found that we can more accurately impute the outcome of the asset test and estimate the number of food stamp eligibles using an accurate estimate of the probability that a household passes the asset test rather than an inaccurate estimate of the household's asset balances.[3]

To most accurately impute the probability of passing the asset test, we partitioned households into three groups:

- *Pure public assistance households*. These households, in which all members receive public assistance, are categorically eligible for food stamps.[4] So, the asset test does not pertain to them.

---

[2]The advantage of richer income and asset data in SIPP is offset by the disadvantage of a weaker sample design for state estimation. For this report, we exploited the relative advantages of the CPS and SIPP, using SIPP to obtain an accurate national total of food stamp eligibles and CPS to, essentially, estimate how that total is distributed across states.

[3]In principle, it might be possible to accurately estimate from imputed asset balances whether a household's assets are above or below the applicable threshold even when the dollar value of assets is poorly estimated, such as when we impute assets of $1,000 when the true value is $500. However, we found that the 6.5 percent rate of return assumption places many households on the wrong side of the threshold, in addition to producing errors in dollar amounts.

[4]Public assistance includes Aid to Families with Dependent Children (AFDC), Supplemental Security Income (SSI), and General Assistance (GA). The procedure for identifying pure public assistance households is described in Cody and Trippe (1997).

- *Income eligible, non-pure public assistance households*. These households are not categorically eligible, but they pass the food stamp gross and net income tests. To be fully eligible, they must pass the asset test.

- *All other households*. These households are not eligible for food stamps because they are not categorically eligible, and their incomes are too high to pass the gross or net income tests.

We set the probability of passing the asset test to one for all households in the first group and to zero for all households in the third group. For the second group, we used a logistic regression model estimated from January 1994 SIPP data to predict the probability that each CPS household in the group passes the asset test. The predictions were based on such characteristics of the household as the age and race of its members, the education and employment status of its members, interest and dividend income, earned income, total income relative to the poverty threshold, and whether the home is owned or rented. In developing the model, we were limited to predictors that were measured in both the SIPP and CPS because the model was estimated from the former and used to make predictions for households in the latter. SIPP data could be used to estimate the model because as noted before, the survey collects information on asset balances, permitting direct measurement of the outcome of the asset test.

For households in each of the three groups, the probability of passing the asset test gives, in fact, the probability of being eligible for food stamps.[5,6] This probability can be used to estimate the

[5]Because a household in the first group is categorically eligible, and a household in the third group is ineligible, the two households are eligible with probabilities one and zero, respectively, which are the assigned probabilities of passing the asset test. For a household in the second group, which consists of income eligible non-pure public assistance households, passing the asset test makes the household fully eligible. Therefore, the probability of passing the asset test is equivalent to the probability of being eligible.

[6]One exception is that the probability of being eligible was set to zero for a household in the first or third group if it does not qualify for at least $1 in food stamp benefits. Another exception is that the probability of being eligible was set to zero for an SSI recipient who receives cash instead of food stamps in an SSI cashout state. (The only such state is California.) We excluded these SSI recipients (continued...)

number of people eligible for food stamps. For example, a person with a sample weight of 1,000 living in a household with a 50 percent chance of being eligible represents 500 (= 0.5 × 1,000) eligible people and 500 (= 0.5 × 1,000) ineligible people. A person with a sample weight of 2,000 living in a household with a 25 percent chance of being eligible represents 500 (= 0.25 × 2,000) eligible people and 1,500 (= 0.75 × 2,000) ineligible people. Together, these two sample members represent 1,000 eligible people, the weighted sum of their probabilities. More generally, a sample estimate of the number of eligibles is obtained by calculating a weighted sum of probabilities across all persons in the sample.[7]

Using this approach, we derived the sample estimates displayed in Table A.2.[8] Rather than calculating counts, we calculated percentages, that is, the percentage of all people in a state that are eligible. Calculating percentages standardized for state size and improved precision.[9]

---

[6](...continued)
when identifying the members of food stamp households.

[7]For estimating the number of eligibles, it is neither necessary nor desirable to impute the outcome of the asset test and, therefore, eligibility status. A common approach to imputing an outcome from an estimated probability is to compare the estimated probability with a uniform random number. If the probability exceeds the random number, the outcome is imputed as having occurred; otherwise, the outcome is imputed as having not occurred. It is easy to see why imputing the outcome of eligibility is not desirable for estimating the number of eligibles. If each of two persons has a 50 percent probability of being eligible and we draw a uniform random number for each, the chances are 25 percent that both are imputed as eligible, 50 percent that just one is imputed as eligible, and 25 percent that neither are imputed as eligible. The expected value for the number imputed as eligible is 1 ($= 0.25 \times 2 + 0.5 \times 1 + 0.25 \times 0$), which is just the sum of the probabilities (0.5 + 0.5). Drawing random numbers simply introduces additional variability into our estimate.

[8]In calculating sample eligibility estimates (but not sample poverty estimates), we used race codes and sample weights that were developed by Jeffrey Passel of The Urban Institute to correct for inconsistencies between the race codes on the CPS public use file and the population estimates that were used by the Census Bureau to create the weights on that file.

[9]Standardization for size is required for the regression and shrinkage estimation performed in the next two steps. If, in those steps, we modeled eligibility counts, we would need to incorporate in the model an explicit size effect capturing the tendency for a more populous state to have more eligible
(continued...)

In addition to our point estimates of eligibility percentages and poverty rates, we need estimates of their sampling variability. We estimated standard errors using the jackknife estimator proposed by Rao, Wu, and Yue (1992), treating CPS rotation groups as clusters. A rotation group, about one-eighth of a monthly CPS sample, consists of a group of households (actually, housing units) that begin the CPS at the same time. They are in the CPS for four months, rotate out for eight months, and rotate back in for four months, after which they are dropped from the CPS.

To obtain jackknife estimates of the standard errors of our poverty estimates, for example, we let Z_i equal the CPS sample estimate of the number of poor people in state i (i = 1, 2, ..., 51) and $Z_{i,r}$ equal the contribution of rotation group r (r = 1, 2, ..., 8) to that estimate. In other words:

$$(1) \qquad Z_i = \sum_{r=1}^{8} Z_{i,r} \; .$$

We also let N_i equal the CPS sample estimate of the population in state i and $N_{i,r}$ equal the contribution of rotation group r to that estimate. That is:

$$(2) \qquad N_i = \sum_{r=1}^{8} N_{i,r} \; .$$

If Y_i equals the CPS sample estimate of the poverty rate in state i:

$$(3) \qquad Y_i = 100 \, \frac{Z_i}{N_i} \; .$$

---

[9](...continued)
people than a less populous state simply because of the difference in population size. No such effect is needed if we model percentages. It is for this reason that we calculated poverty rates, rather than counts, earlier in this step. Estimated percentages and rates are more precise than estimated counts because the sampling errors in the numerators and denominators of percentages/rates tend to be positively correlated and, therefore, partially "cancel out."

TABLE A.2

PERCENTAGES ELIGIBLE FOR FOOD STAMPS IN 1994

	Point Estimate			Standard Error		
State	Sample	Regression	Shrinkage	Sample	Regression	Shrinkage
Alabama	17.8	16.0	16.2	2.1	1.1	1.0
Alaska	11.6	11.1	11.2	1.6	1.7	1.4
Arizona	15.1	14.2	14.4	1.2	0.9	0.7
Arkansas	15.3	14.8	14.9	1.2	1.1	0.8
California	16.8	16.7	16.7	0.5	1.1	0.5
Colorado	8.4	10.1	9.4	0.9	0.9	0.7
Connecticut	10.1	10.0	10.0	2.1	1.2	1.0
Delaware	8.1	10.1	9.6	1.2	1.0	0.8
District of Columbia	25.0	23.4	23.5	3.1	2.0	1.9
Florida	14.9	15.1	15.0	1.0	1.0	0.7
Georgia	14.8	15.8	15.4	1.0	0.9	0.7
Hawaii	8.6	10.2	9.9	1.8	1.1	1.0
Idaho	11.1	9.8	10.2	1.0	1.0	0.7
Illinois	13.8	13.7	13.7	1.3	0.9	0.7
Indiana	11.9	10.3	10.5	2.2	1.0	0.9
Iowa	6.7	9.5	8.8	1.3	0.9	0.8
Kansas	13.4	10.1	11.1	1.2	0.9	0.8
Kentucky	18.0	17.1	17.2	2.3	0.9	0.8
Louisiana	23.0	22.2	22.3	1.7	1.1	0.9
Maine	10.1	10.0	10.0	0.8	1.0	0.6
Maryland	11.9	10.5	10.8	1.6	1.0	0.8
Massachusetts	10.4	10.2	10.3	0.8	0.9	0.6
Michigan	13.3	12.7	13.0	0.9	1.0	0.7
Minnesota	8.5	9.7	9.4	1.3	0.9	0.8
Mississippi	21.5	23.4	23.1	1.9	1.2	1.0
Missouri	14.2	13.0	13.1	2.1	0.9	0.8
Montana	9.3	11.2	10.5	1.0	1.0	0.8
Nebraska	7.1	9.1	8.0	0.7	0.9	0.6
Nevada	11.6	9.3	9.7	1.6	0.9	0.8
New Hampshire	9.1	6.9	7.7	1.0	1.1	0.8
New Jersey	10.3	10.5	10.4	0.8	1.0	0.6
New Mexico	19.0	19.3	19.2	0.8	1.2	0.7
New York	15.7	15.9	15.8	0.6	1.0	0.5
North Carolina	14.3	13.5	13.9	0.9	0.9	0.6
North Dakota	11.0	9.5	10.0	1.0	1.0	0.7
Ohio	14.0	12.9	13.3	1.0	1.0	0.7
Oklahoma	16.3	14.1	14.6	1.4	0.9	0.8
Oregon	12.0	10.2	10.5	2.0	0.9	0.8
Pennsylvania	11.5	11.8	11.6	0.6	0.9	0.5
Rhode Island	11.2	10.1	10.3	1.6	1.0	0.9
South Carolina	14.9	15.3	15.2	1.9	1.0	0.9
South Dakota	11.1	11.4	11.4	2.4	1.0	0.9
Tennessee	16.4	16.8	16.7	1.0	1.0	0.7
Texas	19.2	19.5	19.3	0.4	1.0	0.4
Utah	8.5	8.6	8.6	1.1	1.0	0.7
Vermont	8.1	9.7	9.3	1.3	1.0	0.8
Virginia	9.6	10.0	9.8	0.9	0.9	0.6
Washington	11.2	10.9	11.0	1.0	0.9	0.6
West Virginia	17.8	17.7	17.8	1.0	1.0	0.7
Wisconsin	8.3	9.5	9.1	1.1	0.9	0.7
Wyoming	8.8	9.7	9.4	1.1	0.9	0.7

If we were to exclude the observations in rotation group *r*, we could estimate the poverty rate in state *i* by:

$$(4) \qquad Y_{i(r)} = 100 \; \frac{Z_i - Z_{i,r}}{N_i - N_{i,r}} \; .$$

The "(*r*)" subscript indicates that rotation group *r* has been excluded. By excluding each of the eight rotation groups in turn, we can get eight alternative estimates for the poverty rate in state *i*. Then, we can assess the degree of sampling variability (estimate the variance of Y_i) by measuring the variability among the eight estimates according to:

$$(5) \qquad \mathrm{var}(Y_i) = \frac{7}{8} \sum_{r=1}^{8} (Y_{i(r)} - Y_i)^2 \; .$$

The factor 7/8 enters this expression because the $Y_{i(r)}$ are obtained from samples that are only 7/8 the size of the full CPS sample for state *i* and, hence, are expected to be more variable than Y_i (by a factor of 8/7). Our jackknife estimate of the standard error of Y_i is obtained by taking the square root of var(Y_i). Estimated jackknife standard errors for the sample estimates are presented in Tables A.1 and A.2.

2. Using regression models, predict state poverty rates and food stamp eligibility percentages based on administrative and decennial census data.

While our poverty model predicted poverty rates using NSLP participation, SSI participation, and the 1989 poverty rate as predictors, our food stamp eligibility model used as predictors population size, per capita income, NSLP participation, AFDC participation, the maximum AFDC grant, the maximum AFDC grant squared, the interaction (that is, the product) of AFDC participation and the maximum AFDC grant, and the 1989 poverty rate. In addition to these predictors that we selected for our “best” models, we considered Unemployment Insurance program participation and measures of residential and nonresidential construction as potential predictors. All of the predictors considered had two characteristics: (1) they are, plausibly, good indicators of differences among states in the incidence of poverty, socioeconomic conditions related to poverty, or the health of the economy, and (2) they could be measured uniformly across states from nonsample or highly precise sample data, such as census or administrative records data.[10]

As shown in the next step (where we describe the regression estimation procedure in more detail), we do not have to calculate regression estimates as a separate step, although we do have to select best regression models before we can calculate shrinkage estimates. We selected our best models on the basis of their strong relative performance in predicting poverty rates and eligibility percentages, judging performance by examining functions of the regression residuals, such as mean squared error.

Following the estimation procedure described in the next step, we obtained these estimated regression equations:[11]

$$
\begin{aligned}
\text{Poverty rate} = & + 1.14 \\
& + 0.20 \times \text{NSLP participation} \\
& + 0.62 \times \text{SSI participation} \\
& + 0.29 \times \text{Poverty rate (in 1989)}
\end{aligned}
$$

[10]The three predictors based on the maximum AFDC grant also help to control for the effects of differences in the generosity of state AFDC programs.

[11]The regression equations do not express casual relationships. They do not imply, for example, that more SSI recipients cause more poor people. Rather, the equations imply only statistical associations: states with more SSI recipients typically have more poor people than states with fewer SSI recipients. For this reason, predictors are often called "symptomatic indicators." They are symptomatic of differences among states in conditions associated with having more or fewer poor people.

$$\begin{aligned}
\text{Eligibility percentage} = {} & -3.95 \\
& + 0.00012 && \times \text{Population size} \\
& + 1.26 && \times \text{Per capita income} \\
& + 0.14 && \times \text{NSLP participation} \\
& + 0.51 && \times \text{AFDC participation} \\
& + 0.0044 && \times \text{Maximum AFDC grant} \\
& + 0.000025 && \times \text{Maximum AFDC grant squared} \\
& - 0.0022 && \times (\text{AFDC participation} \times \text{Maximum AFDC grant}) \\
& + 0.37 && \times \text{Poverty rate (in 1989)}
\end{aligned}$$

Definitions and data sources for the predictors in our best regression models are given in Table A.3. Table A.4 displays each state's values for the predictors.[12] Regression estimates and their standard errors were shown earlier in Tables A.1 and A.2 along with the sample estimates calculated in the previous step.

3. Using "shrinkage" methods, average the sample estimates and regression predictions to obtain preliminary shrinkage estimates of state poverty rates/food stamp eligibility percentages.

To average the sample estimates and the regression predictions, we used a Bayesian shrinkage estimator. The estimator does not have a closed-form expression from which we can calculate shrinkage estimates. Instead, we must numerically integrate over the parameter σ, a scalar measuring the lack of fit of the regression model for poverty rates. To perform the numerical integration, we

[12]Values for the maximum AFDC grant squared and AFDC participation times the maximum AFDC grant are not displayed in Table A.4 because they are easily obtained from values that are displayed.

TABLE A.3

DEFINITIONS AND DATA SOURCES FOR PREDICTOR VARIABLES

Predictor Variable[a]	Definition	Principal Data Source
Population size[b]	$\dfrac{\text{Resident population}}{1{,}000}$	Resident population estimates were obtained electronically from file stage95.txt at http://www.census.gov/population/www/statepop.html.
Per capita income[c]	$\dfrac{(\text{Total personal income} \div \text{Resident population})}{\text{Poverty guideline for one-person family}}$	Total personal income amounts were obtained from U.S. Department of Commerce (1996).
NSLP participation[d]	$100 \times \dfrac{\text{Number of children approved for free or reduced-price lunches}}{\text{Resident population of children ages 5-17}}$	NSLP participant counts were obtained by facsimile from the Food and Nutrition Service, U.S. Department of Agriculture.
SSI participation[e]	$100 \times \dfrac{\text{Number of people receiving federally-administered payments}}{\text{Resident population}}$	SSI participant counts were obtained electronically from www.ssa.gov/statistics/ors_home.html.
AFDC participation[e]	$100 \times \dfrac{\text{Number of people receiving cash payments}}{\text{Resident population}}$	AFDC participant counts were obtained by facsimile from the Administration for Children and Families, U.S. Department of Health and Human Services.
Maximum AFDC grant[f]	Maximum grant − Average maximum grant across states	Maximum grant amounts were obtained from U.S. House of Representatives (1994).
Maximum AFDC grant squared	Maximum AFDC grant × Maximum AFDC grant	See above.
AFDC participation times Maximum AFDC grant	AFDC participation × Maximum AFDC grant	See above.
Poverty rate	$100 \times \dfrac{\text{Number of poor people}}{\text{Number of people}}$	Decennial census poverty rates were obtained from U.S. Department of Commerce (1993).

[a]All variables pertain to 1994 except the poverty rate, which pertains to 1989.
[b]Resident population estimates are for July 1, 1994, and are consistent with estimates in Census Bureau Product Announcement CB96-88, issued May 31, 1996.
[c]The poverty guidelines used equal $8950, $8255, and $7165 for Alaska, Hawaii, and the rest of the United States, respectively. Their construction is described in Schirm (1996).
[d]Counts of approved applications are as of October.
[e]Number of recipients are as of December.
[f]Maximum grant amounts are maximum monthly benefits as of January 1994 for a one-parent family with three members.

TABLE A.4

PREDICTOR VARIABLES IN REGRESSION MODELS

State	Resident Population	Per Capita Income	NSLP Participation	SSI Participation	AFDC Participation	Maximum AFDC Grant	Poverty Rate
Alabama	4,220	2.5	43.9	3.8	2.9	-232	18.3
Alaska	603	2.6	22.3	1.1	6.1	527	9.0
Arizona	4,079	2.7	39.8	1.7	4.9	-49	15.7
Arkansas	2,453	2.4	41.3	3.8	2.7	-192	19.1
California	31,408	3.2	41.3	3.2	8.5	211	12.5
Colorado	3,662	3.2	25.6	1.5	3.1	-40	11.7
Connecticut	3,275	4.2	22.4	1.3	5.2	284	6.8
Delaware	708	3.5	30.1	1.5	3.7	-58	8.7
District of Columbia	567	4.4	66.8	3.5	13.1	24	16.9
Florida	13,958	3.0	41.0	2.3	4.6	-93	12.7
Georgia	7,058	2.9	41.4	2.8	5.5	-116	14.7
Hawaii	1,178	2.9	31.7	1.5	5.5	316	8.3
Idaho	1,134	2.5	30.8	1.4	2.1	-79	13.3
Illinois	11,759	3.3	30.2	2.2	6.1	-29	11.9
Indiana	5,755	2.9	25.3	1.5	3.5	-108	10.7
Iowa	2,831	2.8	25.2	1.4	3.7	30	11.5
Kansas	2,551	2.9	30.7	1.4	3.2	33	11.5
Kentucky	3,828	2.5	42.8	4.1	5.1	-168	19.0
Louisiana	4,316	2.5	55.5	4.1	6.0	-206	23.6
Maine	1,239	2.7	28.7	2.4	4.9	22	10.8
Maryland	5,000	3.5	27.7	1.6	4.5	-30	8.3
Massachusetts	6,041	3.7	24.2	2.6	4.8	183	8.9
Michigan	9,492	3.2	27.9	2.2	6.5	63	13.1
Minnesota	4,568	3.2	24.6	1.3	3.7	136	10.2
Mississippi	2,670	2.2	58.0	5.2	5.5	-276	25.2
Missouri	5,279	2.9	30.5	2.1	4.9	-104	13.3
Montana	856	2.5	28.0	1.6	4.0	5	16.1
Nebraska	1,624	2.9	26.7	1.3	2.6	-32	11.1
Nevada	1,462	3.3	25.8	1.3	2.8	-48	10.2
New Hampshire	1,135	3.4	16.8	0.9	2.5	154	6.4
New Jersey	7,903	4.0	26.5	1.8	4.1	28	7.6
New Mexico	1,655	2.4	63.0	2.6	6.4	-39	20.6
New York	18,153	3.7	42.0	3.1	7.0	181	13.0
North Carolina	7,070	2.8	35.3	2.6	4.6	-124	13.0
North Dakota	639	2.5	26.0	1.4	2.3	13	14.4
Ohio	11,104	3.0	26.5	2.1	5.7	-55	12.5
Oklahoma	3,257	2.5	42.0	2.2	3.9	-72	16.7
Oregon	3,087	2.8	28.4	1.5	3.5	64	12.4
Pennsylvania	12,062	3.1	27.4	2.1	5.1	25	11.1
Rhode Island	994	3.1	29.7	2.3	6.3	158	9.6
South Carolina	3,643	2.5	46.2	3.0	3.6	-196	15.4
South Dakota	723	2.6	34.3	1.8	2.5	21	15.9
Tennessee	5,176	2.8	38.1	3.4	5.4	-211	15.7
Texas	18,413	2.8	47.0	2.1	4.3	-212	18.1
Utah	1,909	2.4	27.3	1.0	2.5	18	11.4
Vermont	580	2.8	28.0	2.2	4.7	242	9.9
Virginia	6,551	3.2	27.0	1.9	2.9	-42	10.2
Washington	5,338	3.2	28.0	1.6	5.4	150	10.9
West Virginia	1,824	2.4	45.3	3.5	6.0	-147	19.7
Wisconsin	5,083	3.0	22.9	2.2	4.2	121	10.7
Wyoming	476	2.8	27.8	1.2	3.2	-36	11.9

NOTE: See Table A.3 for definitions of predictor variables.

specified a grid of 126 equally-spaced points, starting with $\sigma = 0.00$ and incrementing by 0.02 up to $\sigma = 2.50$.[13] For σ_k ($k = 1, 2, ..., 126$), we calculated a vector of shrinkage estimates:

$$(6) \qquad \theta_k = (\Sigma_k^{-1} + V^{-1})^{-1}(\Sigma_k^{-1}X\hat{B}_k + V^{-1}Y) \ ,$$

a variance-covariance matrix:

$$(7) \qquad U_k = (\Sigma_k^{-1} + V^{-1})^{-1} + (\Sigma_k^{-1} + V^{-1})^{-1}\Sigma_k^{-1}X(X'(\Sigma_k + V)^{-1}X)^{-1}X'\Sigma_k^{-1}(\Sigma_k^{-1} + V^{-1})^{-1} \ ,$$

and a probability:

$$(8) \qquad p_k^* = |\Sigma_k + V|^{-1/2} \ |X'(\Sigma_k + V)^{-1}X|^{-1/2} \ \exp\left(-\frac{1}{2}(Y - X\hat{B}_k)'(\Sigma_k + V)^{-1}(Y - X\hat{B}_k) \right) .$$

In these expressions, Y is a column vector of sample estimates (from Step 1) with 51 elements, one sample estimate for each of the 51 states. The vector of shrinkage estimates, θ_k , has the same structure as the vector of sample estimates, Y. V is the (51 × 51) variance-covariance matrix for the sample estimates. Because state samples are independent in the CPS, V is diagonal. X is a (51 × 4) matrix, with one row per state containing the values for the three predictors (plus an intercept) in the poverty rate regression model. $\hat{B}_k$ is a (4 × 1) vector of regression coefficients, and is given by:

$$(9) \qquad \hat{B}_k = (X'(\Sigma_k + V)^{-1}X)^{-1}X'(\Sigma_k + V)^{-1}Y \ .$$

Finally, $\Sigma_k = \sigma_k^2 I$, where I is a (51 × 51) identity matrix (all diagonal elements equal one and all other elements equal zero).[14]

---

[13]For estimating eligibility percentages, we specified a grid of 176 equally-spaced points, starting with $\sigma = 0.00$ and incrementing by 0.01 up to $\sigma = 1.75$.

[14]When deriving eligibility estimates, X is a (51 × 9) matrix, with one row per state containing the values for the eight predictors (plus an intercept) in the eligibility percentage regression model. $\hat{B}_k$ is a (9 × 1) vector of regression coefficients. When we integrated over $\sigma_k = 0$ in estimating poverty rates and eligibility percentages, we set $\theta_k = X(X'V^{-1}X)^{-1}X'V^{-1}Y$ and $U_k = X(X'V^{-1}X)^{-1}X'$, their
(continued...)

After calculating θ_k , U_k , and p_k^* 126 times (once for each σ_k), we calculated the probability of σ_k:

$$(10) \qquad p_k = \frac{p_k^*}{\sum_{k=1}^{126} p_k^*} \ ,$$

which is also an estimate of the probability that the shrinkage estimates θ_k are the true values. As Equation (10) suggests, the p_k are obtained by normalizing the p_k^* to sum to one.[15]

To complete the numerical integration over σ and obtain a single set of shrinkage estimates, we calculated a weighted sum of the 126 sets of shrinkage estimates, weighting each set θ_k by its associated probability p_k. Thus, our shrinkage estimates are:

$$(11) \qquad \theta = \sum_{k=1}^{126} p_k \theta_k \ .$$

The variance-covariance matrix is:

$$(12) \qquad U = \sum_{k=1}^{126} p_k U_k + \sum_{k=1}^{126} p_k (\theta_k - \theta)(\theta_k - \theta)' \ .$$

The first term on the right side of this expression reflects the error from sampling variability and the lack of fit of the regression model. The second term captures how the shrinkage estimates vary as σ varies. Thus, the second term accounts for the variability from not knowing and, thus, having to

[14](...continued)
limiting values.

[15]When deriving eligibility estimates, the summations in Equations (10)-(15) run from 1 to 176, reflecting the 176 values of σ .

estimate σ. The standard errors of the shrinkage estimates were calculated by taking the square roots of the diagonal elements of U.

Regression estimates can be similarly obtained. They are:

$$(13) \qquad R = \sum_{k=1}^{126} p_k R_k \ ,$$

where $R_k = X\hat{B}_k$ is the vector of regression estimates obtained when $\sigma = \sigma_k$. The variance-covariance matrix is:

$$(14) \qquad G = \sum_{k=1}^{126} p_k G_k + \sum_{k=1}^{126} p_k (R_k - R)(R_k - R)' \ ,$$

where $G_k = X(X'(\Sigma_k + V)^{-1}X)^{-1}X' + \Sigma_k$. We can estimate the regression coefficient vector by:

$$(15) \qquad \hat{B} = \sum_{k=1}^{126} p_k \hat{B}_k \ .$$

Shrinkage estimates and their standard errors were displayed earlier in Tables A.1 and A.2 along with the sample and regression estimates calculated in the previous two steps.

4. For each state, multiply the preliminary shrinkage estimate of the poverty rate/food stamp eligibility percentage by the state population to obtain a preliminary shrinkage estimate of the number poor/eligible.

We calculated preliminary eligibility counts in the same way that we calculated preliminary poverty counts. These estimates of numbers eligible are displayed in Table A.5, which also displays

TABLE A.5

PRELIMINARY SHRINKAGE ESTIMATES OF THE NUMBERS OF PEOPLE
ELIGIBLE FOR FOOD STAMPS IN 1994

State	Preliminary Shrinkage Estimate of Percentage Eligible	Population	Preliminary Shrinkage Estimate of Number Eligible
Alabama	16.169	4,264,209	689,480
Alaska	11.227	609,589	68,439
Arizona	14.422	4,223,527	609,117
Arkansas	14.910	2,415,571	360,162
California	16.738	31,938,945	5,345,941
Colorado	9.395	3,767,418	353,949
Connecticut	10.042	3,184,167	319,754
Delaware	9.572	678,989	64,993
District of Columbia	23.516	598,332	140,704
Florida	15.035	14,240,277	2,141,026
Georgia	15.429	7,206,311	1,111,862
Hawaii	9.947	1,202,919	119,654
Idaho	10.247	1,137,625	116,572
Illinois	13.708	11,847,816	1,624,099
Indiana	10.465	5,946,196	622,269
Iowa	8.787	2,820,290	247,819
Kansas	11.086	2,517,803	279,124
Kentucky	17.213	3,830,341	659,317
Louisiana	22.324	4,363,502	974,108
Maine	10.031	1,201,585	120,531
Maryland	10.818	5,020,118	543,076
Massachusetts	10.323	5,990,461	618,395
Michigan	12.963	9,499,065	1,231,364
Minnesota	9.377	4,492,799	421,290
Mississippi	23.130	2,571,451	594,777
Missouri	13.103	5,082,954	666,019
Montana	10.480	850,079	89,088
Nebraska	8.029	1,646,540	132,201
Nevada	9.717	1,512,336	146,954
New Hampshire	7.709	1,127,887	86,949
New Jersey	10.384	7,904,784	820,833
New Mexico	19.197	1,715,164	329,260
New York	15.822	18,241,877	2,886,230
North Carolina	13.862	6,904,856	957,151
North Dakota	10.028	635,111	63,689
Ohio	13.335	11,151,847	1,487,099
Oklahoma	14.578	3,231,366	471,069
Oregon	10.480	3,175,316	332,773
Pennsylvania	11.630	11,946,935	1,389,429
Rhode Island	10.345	968,659	100,208
South Carolina	15.233	3,629,526	552,886
South Dakota	11.361	745,957	84,748
Tennessee	16.659	5,343,652	890,199
Texas	19.280	18,904,339	3,644,757
Utah	8.594	1,920,539	165,051
Vermont	9.287	592,832	55,056
Virginia	9.833	6,634,968	652,416
Washington	10.992	5,335,743	586,505
West Virginia	17.750	1,793,243	318,301
Wisconsin	9.115	4,991,605	454,985
Wyoming	9.380	485,749	45,563
United States		262,043,170	36,787,241

estimates of percentages eligible and state population totals. The population totals were estimated directly from the CPS.[16,17]

5. Adjust the preliminary state shrinkage estimates of the numbers poor/eligible to derive final shrinkage estimates that sum to the national total obtained directly from the CPS/SIPP.

In the main text, we described how we derived final poverty estimates. Here, we describe how we derived final eligibility estimates. We also describe how we derived confidence intervals for all of our estimates.

There is just one difference--an important one--in how we adjusted poverty and eligibility estimates to national totals. While the national poverty count was estimated from the CPS, which was the source for all of our state estimates (both poverty and eligibility), the national eligibility count was estimated from the SIPP. For that, we pooled the January 1994 data collected in Wave 7 of the

---

[16]These population totals are slightly different from the population totals reported in Table II.2 that were used in conjunction with our poverty estimates. The reason for the difference concerns the treatment of secondary individuals under age 15 in the CPS sample (mainly foster children according to previous research). Such children are excluded from the poverty universe defined for official government statistical purposes and used by the Census Bureau. Although we have excluded such children from our poverty counts and the associated population totals, we did not exclude them from estimates of food stamp eligibles or from the population totals used with the eligibility estimates.

[17]We obtained our population estimates by summing the sample weights assigned to persons in the CPS sample. Those weights are controlled to population estimates developed by the Census Bureau from census and administrative records (mainly vital statistics) data. In broad terms, the population estimates are derived by subtracting from census counts persons "exiting" the population (due to death or net out-migration) and adding persons "entering" the population (due to birth or net in-migration). The population estimates used to control the sample weights for persons in the March 1995 CPS have been adjusted for the undercount in the 1990 census. These estimates are different from the population estimates published by the Census Bureau, which are not adjusted. By legal agreement, the Census Bureau can use adjusted population estimates only for weighting data collected in its sample surveys. Because CPS sample weights are controlled at the state level to the size of the population of persons ages 16 and over only, the CPS direct sample estimate of the entire state population is subject to some sampling variability, which we ignore later in deriving confidence intervals for our final estimates.

1992 Panel with the January 1994 data collected in Wave 4 of the 1993 Panel and used the MATH® SIPP microsimulation model.[18]

As shown in Table A.5, the preliminary state shrinkage estimates derived in Step 4 summed to 36,787,241 eligibles nationwide. According to our SIPP data and MATH model calculations, there were 37,865,669 eligibles in the entire United States in January 1994. To obtain final shrinkage estimates for states that sum (aside from rounding error) to the SIPP-based national total for eligibles, we multiplied each of the preliminary state shrinkage estimates for eligibles by 37,865,669 ÷ 36,787,241 ($\approx$ 1.0293).

After calculating the adjusted eligibility count for each state, we discovered that there were two states with fewer eligibles than participants, implying participation rates over 100 percent.[19] To cap participation rates at 100 percent, we performed one more adjustment. Specifically, we took eligibles away from the 49 states that had enough (that is, more eligibles than participants) and gave them to the two states that did not have enough, stopping when the number of eligibles in each of those two states equaled the number of participants. Eligibles were taken away from a state in proportion to its number of eligibles. This adjustment, which moved very small numbers of eligibles among states, did not change the national total. Moreover, except for the two states with participation rates initially over 100 percent, this adjustment did not change any state's participation rate by more than one-tenth of a percentage point.

---

[18]MATH (Micro Analysis of Transfers to Households) is a registered trademark of Mathematica Policy Research, Inc.

[19]Maine and Vermont had participation rates of 109 and 131 percent, respectively. These compared with CPS direct sample estimates (after adjustment to the SIPP national total) of 109 and 151 percent for these two states. At 104 percent, the direct sample estimates for Hawaii and Delaware also exceeded 100 percent, although the shrinkage estimates were under 100 percent.

Our final shrinkage estimates of the numbers of people eligible for food stamps were shown earlier in Table III.3 of the main text. Administrative counts of the numbers of people receiving food stamps are displayed in Table A.6.[20] The participation rate for a state was obtained by dividing the (adjusted) number of people participating by the number of people eligible (and multiplying by 100 to obtain a percentage). Participation rates for all states were shown in Table III.3.

In Tables III.2 and III.4 of the main text, we reported approximate 90-percent confidence intervals for our final shrinkage estimates. The upper and lower bounds of the confidence intervals were calculated according to:

$$(16) \qquad \textit{Upper Bound}_i = E_i + 1.645 \; e_i$$

and:

$$(17) \qquad \textit{Lower Bound}_i = E_i - 1.645 \; e_i \; ,$$

where E_i is the final shrinkage estimate for state i and e_i is the standard error of that estimate. For poverty counts and rates, the standard errors are:

$$(18) \qquad e_i = r_p \; N_{p,i} \; \frac{\sqrt{U(i,i)}}{100}$$

and

$$(19) \qquad e_i = r_p \sqrt{U(i,i)} \; ,$$

[20] The unadjusted counts of participants in Table A.6 were obtained from state program operations data. Because these data include the full population of food stamp cases, the unadjusted participant counts are not subject to sampling error. The issuance error rates in Table A.6 were estimated from Integrated Quality Control System (IQCS) sample data and are subject to sampling error, which we ignore in calculating confidence intervals for estimated participation rates. The estimates of participants and issuance error rates--which pertain to January 1994 and federal fiscal year 1994, respectively--were provided to us by the Food and Consumer Service (FCS). The adjusted number of participants for a state equals the unadjusted number times *(1 − error rate/100)*.

TABLE A.6

ADMINISTRATIVE COUNTS OF THE NUMBERS OF
PEOPLE RECEIVING FOOD STAMPS IN JANUARY 1994

State	Unadjusted Number of Participants	Issuance Error Rate (Percent)	Adjusted Number of Participants
Alabama	562,557	2.59	547,987
Alaska	27,527	3.81	26,478
Arizona	515,375	5.74	485,792
Arkansas	290,527	1.19	287,070
California	3,192,996	1.63	3,140,950
Colorado	272,852	2.73	265,403
Connecticut	221,460	2.10	216,809
Delaware	60,009	2.16	58,713
District of Columbia	86,474	0.97	85,635
Florida	1,500,981	4.36	1,435,538
Georgia	820,436	2.29	801,648
Hawaii	112,036	1.58	110,266
Idaho	83,275	3.74	80,161
Illinois	1,195,209	2.15	1,169,512
Indiana	538,224	6.79	501,679
Iowa	197,939	3.15	191,704
Kansas	192,353	2.71	187,140
Kentucky	530,264	1.00	524,961
Louisiana	764,392	0.78	758,430
Maine	137,049	1.76	134,637
Maryland	381,953	2.09	373,970
Massachusetts	441,072	1.34	435,162
Michigan	1,037,232	2.44	1,011,924
Minnesota	317,421	1.18	313,675
Mississippi	523,278	3.45	505,225
Missouri	599,397	3.54	578,178
Montana	72,508	1.87	71,152
Nebraska	111,737	4.34	106,888
Nevada	97,877	2.41	95,518
New Hampshire	62,166	5.42	58,797
New Jersey	542,241	1.95	531,667
New Mexico	246,979	2.96	239,668
New York	2,133,122	2.21	2,085,980
North Carolina	640,024	2.46	624,279
North Dakota	46,864	2.09	45,885
Ohio	1,263,401	3.92	1,213,876
Oklahoma	378,534	3.32	365,967
Oregon	286,710	4.40	274,095
Pennsylvania	1,199,368	2.81	1,165,666
Rhode Island	93,569	1.26	92,390
South Carolina	393,604	1.60	387,306
South Dakota	54,900	1.06	54,318
Tennessee	750,116	2.46	731,663
Texas	2,770,359	4.93	2,633,780
Utah	129,775	3.00	125,882
Vermont	75,580	2.00	74,068
Virginia	544,767	5.41	515,295
Washington	462,496	3.07	448,297
West Virginia	329,904	5.95	310,275
Wisconsin	332,323	1.51	327,305
Wyoming	33,616	2.32	32,836
United States	27,654,828	2.95	26,839,011

respectively, where r_p is the ratio used to adjusted preliminary state estimates to the desired national total ($\approx$ 1.0471, as reported in the main text), $N_{p,i}$ is the population estimate used to calculate poverty estimates for state i, and $U(i,i)$ is the (i,i) diagonal element of U, which was calculated in Step 3. Our estimate of e_i does not take account of the correlation between r_p and our preliminary shrinkage estimates for states, which are summed to obtain the denominator of r_p. Instead, r_p is treated as a constant. For food stamp eligibility counts and participation rates, the standard errors are:

(20) $$e_i = r_f \, N_{f,i} \, \frac{\sqrt{U(i,i)}}{100}$$

and

(21) $$e_i = \frac{participation\ \ rate_i}{eligibility\ \ count_i} \times standard\ \ error\ \ of\ \ eligibility\ \ count_i\ ,$$

respectively, where r_f is the ratio used to adjusted preliminary state estimates to the desired national total ($\approx$ 1.0293) and $N_{f,i}$ is the population estimate used to calculate eligibility estimates for state i.